

Data Mining and Machine Learning for Political Events

An Application to Produce Indicators for Presidential Systems

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Introduction

Data Mining and Machine Learning

Employing a strategy based on **Natural Language Processing** (NLP) and a **text-as-data approach**, this paper presents an entirely novel dataset constructed by applying data mining and machine learning techniques.

The dataset contains detailed information on cabinet turnover in **12 presidential cabinets in Latin America from the mid-1970s to the early 2020s**. The indicators on resignation calls and reallocations of cabinet members are entirely novel.

I focus on the creation of the dataset using Optical Character Recognition (OCR) on press report archives together with machine learning models. The models permitted the training of ensemble **semi-supervised classifiers over a period of almost 50 years**.

Creation of the Dataset

Creation of the Dataset

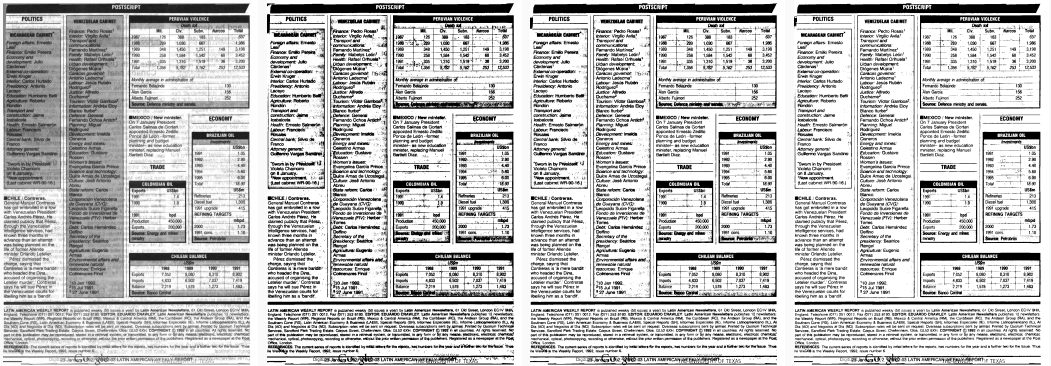
I combined the **Tesseract OCR** (Ooms, 2021) with different **semi-supervised machine learning models** to distinguish between resignation calls and other mentions of cabinet members in the press.

This was applied to **Latin American Weekly Report (LAWR) archives**.

Detail of the Batches of LAWR Archives

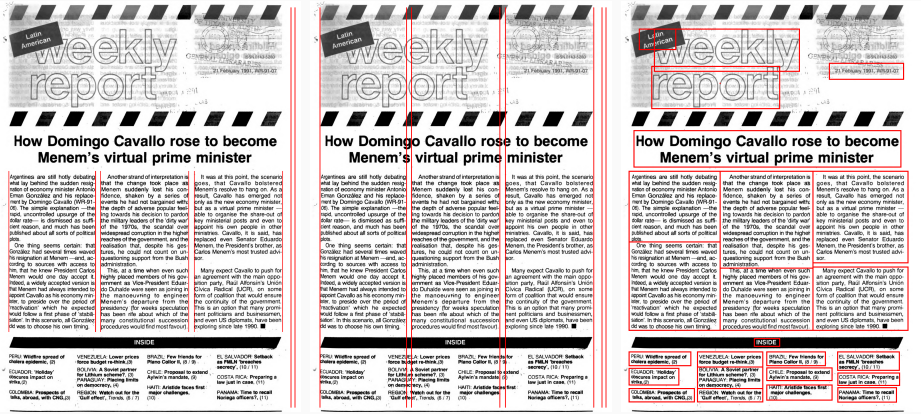
Batch	Archives	Years	Format	Volume
Batch-01	LAWR-1975 to LAWR-1979 Including 1997	5	CSV UTF-8	9.56 MB
Batch-02	LAWR-1980 to LAWR-1998 Excluding 1997 Including the first half of 2003	18.5	PNG images	38.5 GB
Batch-03	LAWR-1999 to LAWR-2021 Excluding the first half of 2003	22.5	PDF files	341 MB

Binarisation Techniques for Enhancing OCR



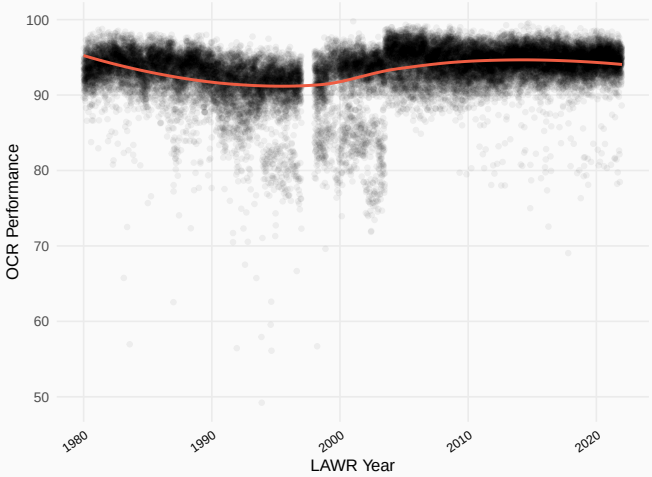
Note. The images correspond to a LAWR page before binarisation and after the application of the techniques of Sauvola and Pietikäinen (2000), Singh et al. (2011) and Su et al. (2010).

Tesseract's Layout Analysis Module



Tab-Stop Lines — Column Layout — Segmented Blocks

Performance and Accuracy of the Tesseract OCR Algorithm



Accuracy is based on the proportion of text that was correctly identified.

This calculation was performed after extracting stop words and carried out with dictionaries trained with **Long Short-Term Memory (LSTM) models** used by Tesseract.

Machine Learning Classifiers

Semi-Supervised Approach

There are two significant **drawbacks** to training **supervised algorithms**:

1. This would have required a major amount of labelled text data **(time and resources)**
2. The accuracy of the algorithms is expected to decrease out-of-the-sample and over time **(batches of archives cover almost 50 years)**

Therefore, I preferred a **semi-supervised approach** that could maintain a **high accuracy level over time with a small amount of coded data** for training (Lee et al., 2021).

1. I drew a subsample of 1,000 LAWR press releases
2. A team of human coders classified all these observations (**resignation calls**)
3. Labelling was conducted to generate ground-truth labels to cross-validate
4. Semi-supervised models using knowledge-based seed words

Semi-Supervised Approach

Pre-processing

80% of the subsample for training

20% for validation

100 tokens per news item *

SMART stop words **

Customised list ***

Stemming algorithm

* until 500 for robustness checks

** Snowball for robustness checks

*** based on LAWR numbering

Models

Naïve Bayes (NB)

Support Vector Machine (SVM) *

Radial Basis Function (RBF) SVM **

Random Forest with 100 trees (RF100)

Random Forest with 500 trees (RF500)

Extreme Gradient Boosting (XGBoost)

* Kernel-based Linear

** Kernel-based Gaussian

Labelling Process for Benchmarking Supervised Models

Coder	Labels	$M(T)$ Label	$\sum$ Time	Consensus
1	966	39s	10h 25m	94.05
2	718	1m 15s	15h 0m	94.84
3	704	38s	7h 29m	94.82
4	318	1m 4s	5h 38m	95.47
5	263	17s	1h 14m	99.26
6	101	1m 17s	2h 9m	88.50

Note. Each observation was hand-coded by three different coders. 2.3% of observations were revised and relabelled during an iteration step. Seed words coincide with features extracted from the benchmarking supervised models trained based on this labelling process.

Goodness-of-Prediction of the Semi-Supervised Models

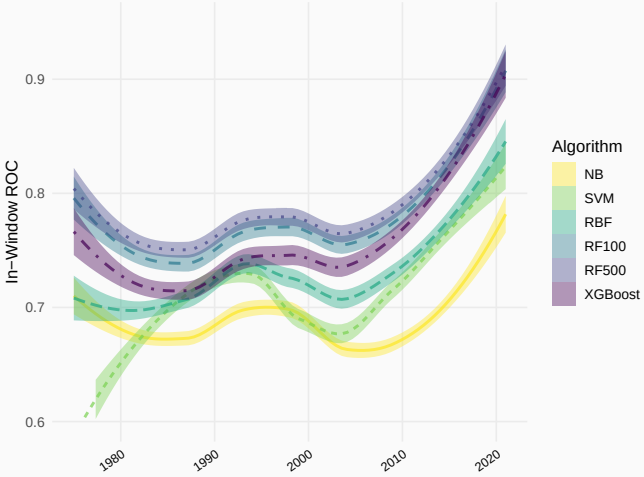
Model	Knowledge-Based Seed Words				
	Accuracy	Precision	Recall	F1-score	ROC
Naïve Bayes	0.713	0.734	0.948	0.828	0.638
Kernel Linear SVM	0.698	0.741	0.900	0.812	0.614
Kernel Gaussian RBF SVM	0.726	0.728	0.995	0.840	0.647
Random Forest (100 trees)	0.743	0.742	0.991	0.849	0.671
Random Forest (500 trees)	0.743	0.740	0.997	0.849	0.682
XGBoost	0.726	0.762	0.905	0.827	0.660

Note. The evaluation was performed with resampling methods using the testing set and 10-fold cross-validation.

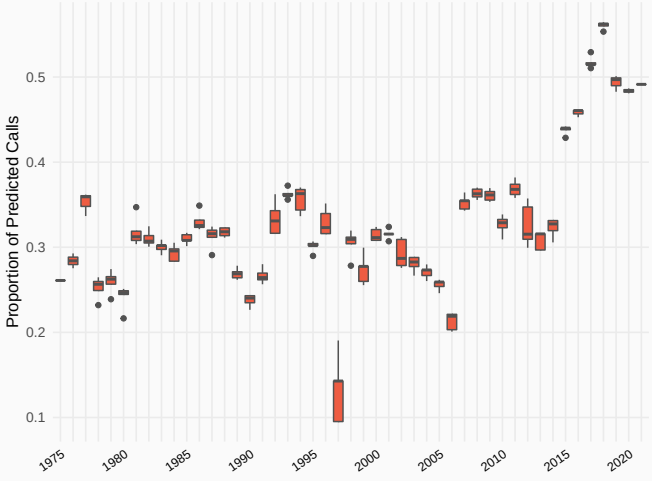
ROC Semi-Supervised Models to Classify Ministerial Resignation Calls

Following a strategy similar to Greene et al. (2019), I used a **five-year fixed rolling window**.

ROC indicators were 10-fold cross-validated in the five-year rolling window testing set between 1975 and 2021.



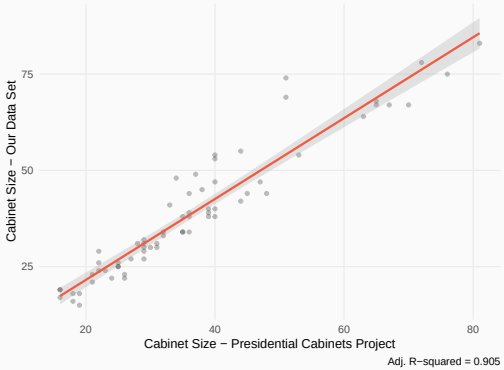
Predicted Ministerial Resignation Calls over Cabinet Press Mentions

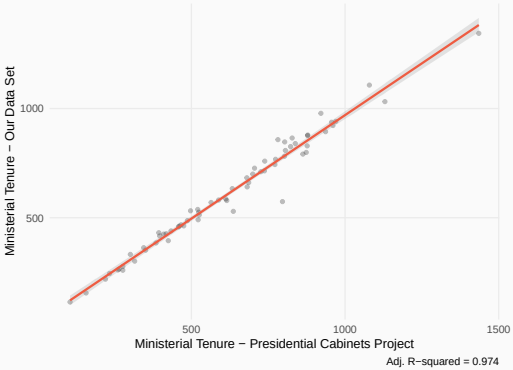


Proportion of predicted resignation calls over mentions of cabinet members in press reports, were carried out with an **ensemble semi-supervised RF500 algorithm**.

Assessing Dataset Validity

Plausibility Checks against Similar Datasets

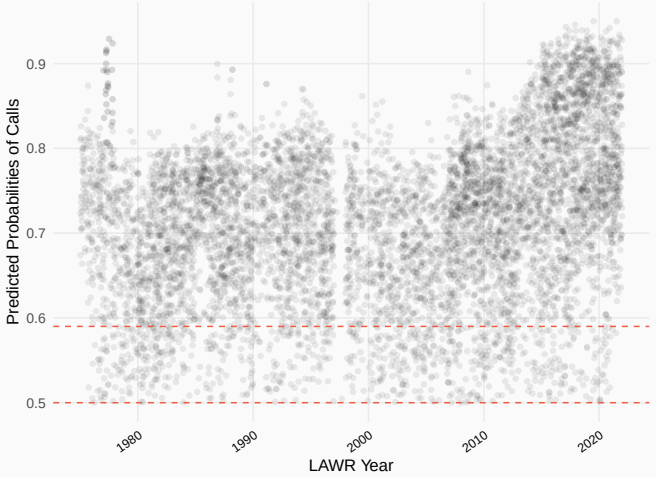




Note. Concurrent presidential terms were used for comparisons with the Presidential Cabinet Project (see Camerlo and Martínez-Gallardo, 2020).

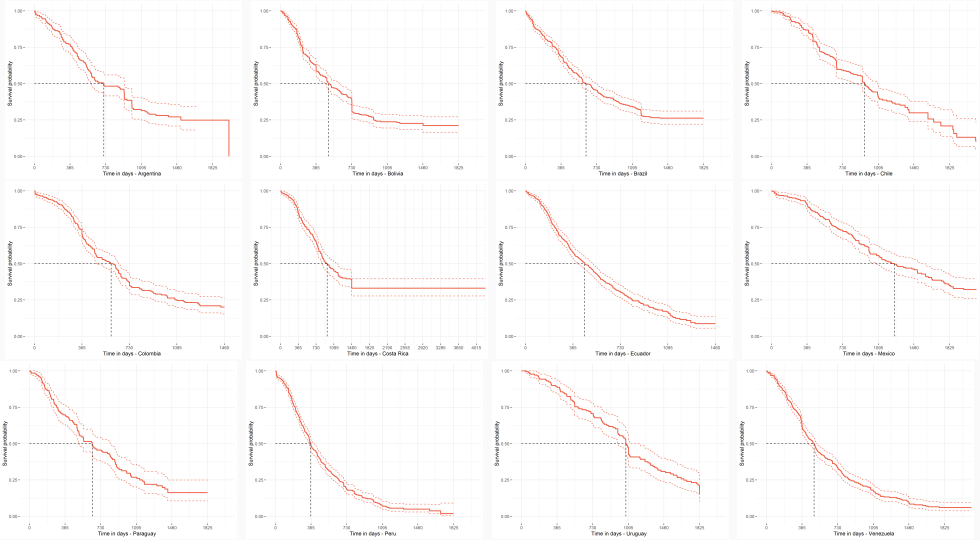
Augmented Artificial Intelligence

I performed an augmented artificial intelligence process based on a **human review** of the predicted observations with low confidence values to improve the data's quality.

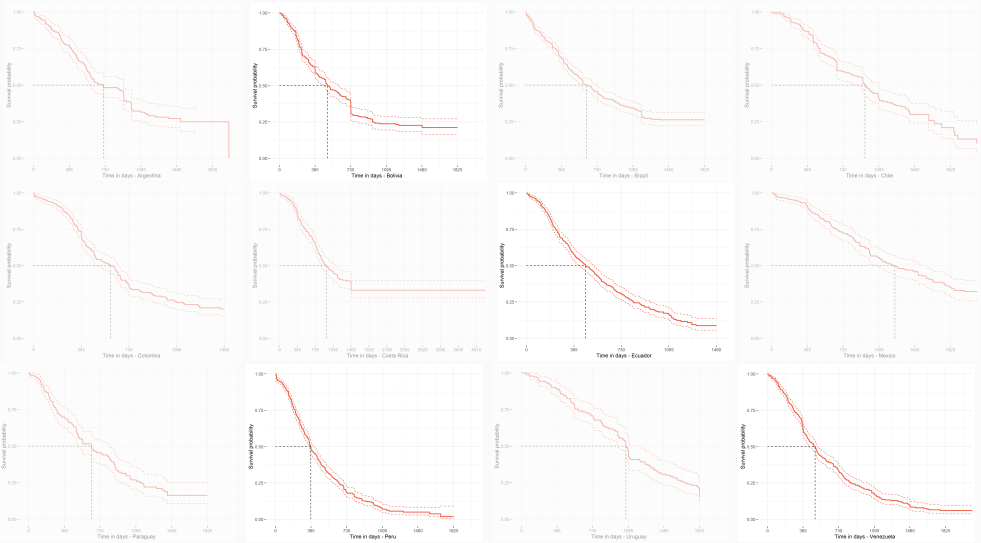


Potential Applications

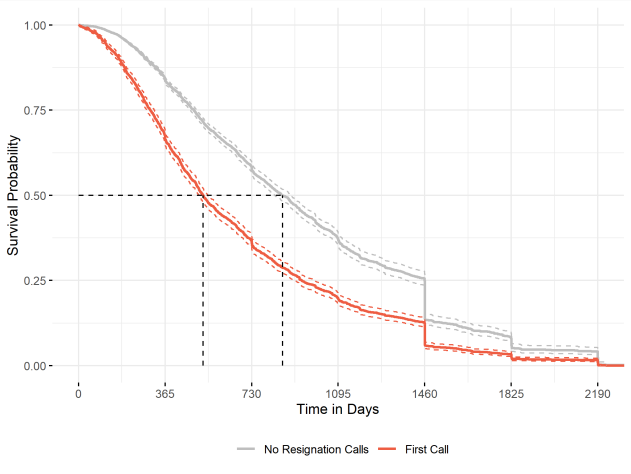
Kaplan-Meier Survival Estimations in 12 Presidential Cabinets



Kaplan-Meier Survival Estimations in 12 Presidential Cabinets



Kaplan-Meier Survival Estimation

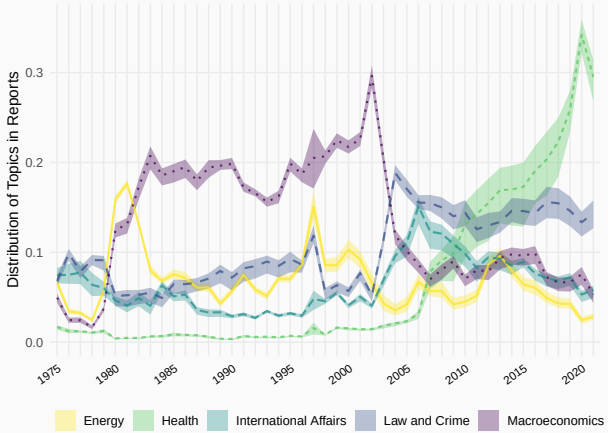


$F(t) = 1 - S(t) = Pr(T \leq t)$ can be used to obtain the incidence of ministerial exits during T by considering $S(t)$ as a survival function, if raw exit is considered an event in the **absence of competing risks**.

Evolution of Major Agenda Topics in Latin America

I used **Keyword Assisted Topic Modelling** (**keyATM**; see Eshima et al., 2022) and a dictionary based on Comparative Agendas Project (2022).

It is a semi-supervised Bayesian application that allows me to obtain ϑ (distribution of topics in the documents and CIs).



Take Aways

Take Aways

☑ To date, this is one of the **most extensive datasets available on presidential cabinets**, going beyond most existing data that tend to focus only on reshuffles or individual ministerial terminations.

☑ With semi-supervised models, **a high level of accuracy** can be obtained from a **small amount of training data** (Lee et al., 2021; Watanabe, 2018; Watanabe and Zhou, 2022).

☑ Additional manual labelling work would be necessary to **identify the source of the questioning** (i.e., opposition leaders, internal disagreements, etc.) This opens new avenues for research on specific dynamics depending on the type of scandal.

☑ Considering the impressive development and leap forward in AI during recent years, **new classifiers could be trained** using generate transformers and LLMs.

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Thank you very much!

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